

Manuscript Number: AGRFORMAT-D-14-00328R2

Title: Estimation of crop gross primary production (GPP): II. Do scaled MODIS vegetation indices improve performance?

Article Type: Research Paper

Section/Category: Plant physiology, Crop Modelling, water relations including evapotranspiration, WUE, interception

Keywords: Daily GPP, MODIS, Vegetation Index, fAPARchl

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Abstract: Satellite remote sensing estimates of Gross Primary Production (GPP) have routinely been made using spectral Vegetation Indices (VIs) over the past two decades. The Normalized Difference Vegetation Index (NDVI), the Enhanced Vegetation Index (EVI), the green band Wide Dynamic Range Vegetation Index (WDRVI_{green}), and the green band Chlorophyll Index (CI_{green}) have been employed to estimate GPP under the assumption that GPP is proportional to the product of VI and photosynthetically active radiation (PAR) (where VI is one of four VIs: NDVI, EVI, WDRVI_{green}, or CI_{green}). However, the empirical regressions between VI*PAR and GPP measured locally at flux towers do not pass through the origin (i.e., the zero X-Y value for regressions). Therefore they are somewhat difficult to interpret and apply. This study investigates (1) what are the scaling factors and offsets (i.e., regression slopes and intercepts) between the fraction of PAR absorbed by chlorophyll of a canopy (fAPARchl) and the VIs, and (2) whether the scaled VIs developed in (1) can eliminate the deficiency and improve the accuracy of GPP estimates. Three AmeriFlux maize and soybean fields were selected for this study, two of which are irrigated and one is rainfed. The four VIs and fAPARchl of the fields were computed with the MODerate resolution Imaging Spectroradiometer (MODIS) satellite images. The GPP estimation performance for the scaled VIs was compared to results obtained with the original VIs and evaluated with standard statistics: the coefficient of determination (R^2), the root mean square error (RMSE), and the coefficient of variation (CV). Overall, the scaled EVI obtained the best performance. The performance of the scaled NDVI, EVI and WDRVI_{green} was improved across sites, crop types and soil/background wetness conditions. The scaled CI_{green} did not improve results, compared to the original CI_{green}. The scaled green band indices (WDRVI_{green}, CI_{green}) did not exhibit superior performance to either the scaled EVI or NDVI in estimating crop daily GPP at these agricultural fields. The scaled VIs are more physiologically meaningful than original un-scaled VIs, but scaling factors and offsets may vary across crop types and surface conditions.

Highlights

- Scale factor and offset are derived with linear regression of fAPAR_{chl} vs. VI
- Scaled NDVI, EVI and WDRVI_{green} improve performance
- Scaled EVI exhibits the best performance
- Scale factor and offset vary with crop types and surface conditions

1 Estimation of crop gross primary production (GPP)

2 II. Do scaled MODIS vegetation indices improve performance?

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31 ***Abstract*** –Satellite remote sensing estimates of Gross Primary Production (GPP) have routinely
32 been made using spectral Vegetation Indices (VIs) over the past two decades. The Normalized
33 Difference Vegetation Index (NDVI), the Enhanced Vegetation Index (EVI), the green band
34 Wide Dynamic Range Vegetation Index ($\text{WDRVI}_{\text{green}}$), and the green band Chlorophyll Index
35 (CI_{green}) have been employed to estimate GPP under the assumption that GPP is proportional to
36 the product of VI and photosynthetically active radiation (PAR) (where VI is one of four VIs:
37 NDVI, EVI, $\text{WDRVI}_{\text{green}}$, or CI_{green}). However, the empirical regressions between VI*PAR and
38 GPP measured locally at flux towers do not pass through the origin (i.e., the zero X-Y value for
39 regressions). Therefore they are somewhat difficult to interpret and apply. This study
40 investigates (1) what are the scaling factors and offsets (i.e., regression slopes and intercepts)
41 between the fraction of PAR absorbed by chlorophyll of a canopy ($f\text{APAR}_{\text{chl}}$) and the VIs, and (2)
42 whether the scaled VIs developed in (1) can eliminate the deficiency and improve the accuracy
43 of GPP estimates. Three AmeriFlux maize and soybean fields were selected for this study, two of
44 which are irrigated and one is rainfed. The four VIs and $f\text{APAR}_{\text{chl}}$ of the fields were computed
45 with the MODerate resolution Imaging Spectroradiometer (MODIS) satellite images. The GPP
46 estimation performance for the scaled VIs was compared to results obtained with the original VIs
47 and evaluated with standard statistics: the coefficient of determination (R^2), the root mean
48 square error (RMSE), and the coefficient of variation (CV). Overall, the scaled EVI obtained the
49 best performance. The performance of the scaled NDVI, EVI and $\text{WDRVI}_{\text{green}}$ was improved
50 across sites, crop types and soil/background wetness conditions. The scaled CI_{green} did not
51 improve results, compared to the original CI_{green} . The scaled green band indices ($\text{WDRVI}_{\text{green}}$,
52 CI_{green}) did not exhibit superior performance to either the scaled EVI or NDVI in estimating crop
53 daily GPP at these agricultural fields. The scaled VIs are more physiologically meaningful than

54 original un-scaled VIs, but scaling factors and offsets may vary across crop types and surface
55 conditions.

56 **Key Words – Daily GPP, MODIS, Vegetation Index, fAPAR_{chl}**

57

58 **I. INTRODUCTION**

59 Atmospheric general circulation models require quantification of land-atmosphere
60 exchanges of energy, water and momentum, including CO₂ fluxes which can be provided by land
61 surface process models (Bonan et al., 2011; Dickinson et al., 1993; Sellers et al., 1986). Satellite
62 remote sensing offers inputs such as land cover types and the Normalized Difference Vegetation
63 Index (NDVI) (Deering, 1978; Tucker, 1979) for use in the land surface modeling (Dickinson et
64 al., 1990; Sellers et al., 1994). Pioneering work (Asrar et al., 1992; Myneni et al., 1997; Running
65 et al., 2000; Sellers, 1987) has shown the fraction of photosynthetically active radiation (PAR)
66 absorbed by a canopy/vegetation (FPAR, i.e., fAPAR_{canopy}) can be approximated with NDVI
67 (Running et al., 2000). Therefore, NDVI has been employed to estimate vegetation Gross
68 Primary Productivity (GPP) in a variation (as GPP=ε*NDVI*PAR, Running et al., 2000),
69 inspired by the logic from the Light Use Efficiency (LUE) model (Monteith, 1972, 1977):

70
$$GPP = \epsilon * fAPAR_{PSN} * PAR = \epsilon * APAR_{PSN}, \quad (1)$$

71 where ε is LUE for vegetation photosynthesis (PSN) (Running et al., 2000) and fAPAR_{PSN} is the
72 fraction of PAR absorbed for PSN (APAR_{PSN}). Monitoring changes in crop GPP with satellite
73 remote sensing data advances the capability to understand and manage global food security,
74 sustainability practices, and environmental impacts, and to study global carbon cycle and global
75 water cycle.

76 The three-band Enhanced Vegetation Index (EVI) (Huete et al., 1997) and the two-band
77 EVI (called EVI2, Jiang et al., 2008) have also been utilized to predict terrestrial GPP in a
78 similar way as $GPP = \epsilon * EVI * PAR$ (Jin et al., 2013; Kalfas et al., 2011; King et al., 2011; Li et al.,
79 2007; Mahadevan et al., 2008; Schubert et al., 2012; Sjöström et al., 2011; Wu et al., 2008, 2010,
80 2011, 2012; Xiao et al., 2004; Yan et al., 2009). In addition, Gitelson and colleagues also
81 explored the application of the green band Wide Dynamic Range Vegetation Index (WDRVI_{green})
82 and the green band Chlorophyll Index (CI_{green}) for crop GPP estimation, in addition to the NDVI
83 and EVI (Gitelson et al., 2008, 2012; Peng and Gitelson, 2011, 2012; Peng et al., 2011).

84 However, since the empirical regressions between the VI*PAR products and GPP
85 measured locally at flux towers do not pass through the origin (i.e., the zero X-Y value for
86 regressions) and produce offsets, they are somewhat difficult to interpret and apply (Gitelson et
87 al., 2012; Sims et al., 2006; Zhang et al., 2014b). This is considered to be a source of error
88 affecting the accuracy and reliability of remote sensing GPP estimates based on VIs. In the
89 literature, there is no paper that presents how to scale the VIs in space and time to solve the
90 problem.

91 The standard MODerate resolution Imaging Spectroradiometer (MODIS) 8-day GPP
92 product (MOD17A2 GPP) uses the MOD15A2 FPAR (a fAPAR_{canopy}) product as a model input
93 (Running et al., 2004; Zhao and Running, 2008). Investigations to find the scaling factor and
94 offset of NDVI through fAPAR_{canopy} – NDVI functions have been conducted, where fAPAR_{canopy}
95 = $a_0 * NDVI + b_0$ (a_0 is the scaling factor or slope, and b_0 is y intercept or offset) (Fensholt et al.,
96 2004; Goward and Huemmrich, 1992; Knyazikhin et al., 1998, 2002; Potter et al., 1993; Prince
97 and Goward, 1995; Randerson et al., 1996; Sellers et al., 1996; Sims et al., 2005). However, the
98 MOD15A2 FPAR product overestimates *in-situ* fAPAR_{canopy} during spring greenup and fall

99 senescent periods, and underestimates *in-situ* fAPAR_{canopy} in mid-summer during peak GPP
100 activity at the agricultural fields we selected [see (Zhang et al., 2014a) for details].

101 We developed an algorithm to retrieve the fraction of PAR absorbed by chlorophyll
102 throughout the canopy (fAPAR_{chl}) from actual MODIS observations or from synthesized 30 m
103 MODIS-spectral-like observations simulated with EO-1 Hyperion images (Zhang, 2003; Zhang
104 et al., 2005, 2009, 2012, 2013, 2014c). We found that fAPAR_{chl} ≠ fAPAR_{canopy}, and that the
105 fraction of PAR absorbed by foliage non-chlorophyll components (fAPAR_{non-chl}) varies with
106 types and seasonally (Zhang et al., 2013). Zhang et al. (2014a) presented the performance of
107 fAPAR_{chl} and MOD15A2 FPAR in crop GPP estimation, and concluded that fAPAR_{chl} is
108 superior to MOD15A2 FPAR. Zhang et al. (2014b) investigated the performance of original un-
109 scaled VIs in GPP estimation, and suggested that further investigation on the performance of
110 scaled VIs should be carried out.

111 The objectives of this paper are straightforward: 1] to explore how surface conditions
112 affect the scaling factors (“a”) and offsets (“b”) derived through regression analysis of fAPAR_{chl}
113 vs. the four VIs: fAPAR_{chl} = a*VI + b for each crop type (corn, soybean) per field; 2] to investigate
114 how much the scaled VIs can improve the prediction accuracy of GPP estimates compared to the
115 prediction of original un-scaled VIs.

116

117 II. METHODS

118 II.1 Study sites and tower data

119 The three AmeriFlux crop sites for corn, or maize (*Zea mays* L.) and soybean (*Glycine*
120 *max* [L.] Merr.) used in this study are located at the University of Nebraska–Lincoln (UNL)

121 Agricultural Research and Development Center near Mead, Nebraska (US-NE1, US-NE2 and
122 US-NE3). The first two fields are circular (radius ~ 390 m) and equipped with center-pivot
123 irrigation systems (US-NE1, $41^{\circ}09'54.2''N$, $96^{\circ}28'35.9''W$; US-NE2, $41^{\circ}09'53.6''N$,
124 $96^{\circ}28'07.5''W$). The third is a 790 m long square field (US-NE3, $41^{\circ}10'46.7''N$,
125 $96^{\circ}26'22.4''W$) that relies entirely on rainfall. Each field is equipped with an eddy covariance
126 flux tower (Gitelson et al., 2012; Gitelson et al., 2006; Peng et al., 2013). The first field (US-NE1)
127 is a continuous maize field while the other two fields are maize-soybean rotation fields (soybean
128 is planted in even years).

129 Tower eddy-covariance carbon exchange, PAR, and GPP measurements in growing
130 season from 2001- 2006 are publically available and can be downloaded from
131 <ftp://cdiac.ornl.gov/pub/ameriflux/data>. The nighttime ecosystem respiration/temperature Q₁₀
132 relationship was used to estimate the daytime ecosystem respiration (Baldocchi, 2003). Daily
133 GPP was computed by subtracting respiration (R) from net ecosystem exchange (NEE), i.e.,
134 GPP=NEE-R (Suyker et al., 2005). These sites provided the opportunity to examine the semi-
135 empirical relationships between fAPAR_{chl} versus VIs for both C4 (maize) and C3 (soybean)
136 crops in both irrigated and non-irrigated ecosystems, and to investigate the benefits of employing
137 the scaled relationships to estimate GPP.

138 II.2 Remote sensing data processing and GPP estimation

139 Six years (2001-2006) of MODIS L1B calibrated radiance data (MOD021KM and
140 MOD02HKM) and geolocation data (MOD03) covering the three study sites were downloaded
141 from <https://ladsweb.nascom.nasa.gov:9400/data/>. Two of the MODIS bands have a nadir spatial
142 resolution of 250 m: B1 (red, 620 – 670 nm) and B2 (near infrared, NIR₁, 841 – 876 nm). The
143 MODIS land bands 3 - 7 have a nadir spatial resolution of 500 m: B3 (blue, 459 – 479 nm), B4

144 (green, 545 – 565 nm), B5 (NIR₂, 1230 – 1250 nm), B6 (shortwave infrared, SWIR₁, 1628 –
145 1652 nm) and B7 (SWIR₂, 2105 – 2155 nm). The centers of the original 500 m grids defined in
146 the standard surface reflectance product (MOD09) that encompass the three tower sites are not
147 the centers of the three fields and vegetation in each of the original 500 m grids is not
148 homogeneous [see Figure 2 of (Guindin-Garcia et al., 2012)]. The MODIS gridding procedure
149 for the standard MOD09 product does not ensure the gridded surface reflectance covers the
150 entire grid (Wolfe et al., 1998). A modified gridding procedure was used for this study (Zhang et
151 al., 2014b), whereby the centers of the three 500 m grids were matched to the centers of the three
152 fields, respectively. The L1B radiance data from each swath were gridded at 500 m resolution for
153 MODIS bands 1-7 with area weight of each MODIS observation. This modified gridding
154 processing was incorporated into the Multi-Angle Implementation of Atmospheric Correction
155 (MAIAC) algorithm (Lyapustin et al., 2008, 2011a, b, 2012). MAIAC is an advanced algorithm
156 which uses time series analysis and a combination of pixel-based and image-based processing to
157 improve cloud/snow detection, and to achieve more accurate aerosol retrievals and atmospheric
158 correction, based on the bidirectional reflectance distribution function (BRDF) model of the
159 surface.

160 Derived bidirectional reflectance factors (BRF, also called directional surface reflectance)
161 in MODIS bands 1-7 were used for this study. The impact of MODIS observation footprint size
162 resulting from variable view zenith angle (VZA) on crop daily GPP estimation for these sites
163 was recently reported elsewhere (Zhang et al., 2014b). In order to eliminate the potential bias due
164 to large VZAs, only observations with VZA $\leq 35^{\circ}$ were included in this study. The surface
165 reflectance data (ρ) were used to calculate the following indices (Deering, 1978; Gitelson, 2004;
166 Gitelson et al., 2007, 2012; Huete et al., 1997, 2002; Tucker, 1979):

$$167 \quad CI_{green} = \frac{\rho_{NIR_1}}{\rho_{green}} - 1 \quad (2)$$

$$WDRVI_{green} = \frac{0.3\rho_{NIR_1} - \rho_{green}}{0.3\rho_{NIR_1} + \rho_{green}} + \frac{1-0.3}{1+0.3} \quad (3)$$

$$169 \quad NDVI = \frac{\rho_{NIR_1} - \rho_{red}}{\rho_{NIR_1} + \rho_{red}} \quad (4)$$

$$170 \quad EVI = 2.5 \frac{\rho_{NIR_1} - \rho_{red}}{1 + \rho_{NIR_1} + 6\rho_{red} - 7.5\rho_{blue}} \quad (5)$$

We used the PROSAIL2 model (Jacquemoud and Baret, 1990; Baret and Fourty, 1997; Braswell et al., 1996; Verhoef, 1984, 1985; Zhang et al., 2005, 2009, 2012, 2013), a coupled soil-canopy-leaf radiative transfer model, to retrieve fAPAR_{chl}, the fraction of PAR absorbed by the foliage of the canopy (fAPAR_{foliage}), and the fraction of PAR absorbed by the non-photosynthetic foliage components (fAPAR_{non-chl}) (Zhang et al., 2014a). A pixel is composed of canopy and soil (Zhang et al., 2009, 2012, 2013). The canopy is partitioned into foliage and stem (including branch), and the foliage component is further partitioned into chlorophyll (chl) and non-chlorophyll (non-chl) components, where non-chl is composed of non-photosynthetic pigments (referred to as brown pigment) and dry matter (Baret and Fourty, 1997). The surface reflectances of MODIS bands 1 – 7 are used for retrieval of fAPAR variables (Zhang et al., 2009, 2012, 2013, 2014c):

$$fAPAR_{non-chl} = fAPAR_{brown_pigment} + fAPAR_{dry_matter} \quad (6)$$

$$fAPAR_{foliage} = fAPAR_{chl} + fAPAR_{non-chl} \quad (7)$$

$$fAPAR_{canopy} = fAPAR_{foliage} + fAPAR_{stem} \quad (8)$$

185 The scaling factors (“a”) and offsets (“b”) of VIs were derived from linear regression through
186 fAPAR_{chl} – VI functions for each crop type per field, where fAPAR_{chl} =a*VI+b (VIs=NDVI,
187 EVI, WDRVI_{green}, and CI_{green}).

188 The product of VIs and tower daily PAR (VI*PAR) and the product of scaled VIs and
189 daily PAR (scaled VI*PAR) were compared against the tower daily GPP for each crop type per
190 field (GPP=ε₀*VI*PAR or GPP=ε̄ *scaled VI*PAR). The coefficients “ε₀” and “ε̄” were
191 computed with a least squares best fit algorithm. The computed values for ε₀ and ε̄ were then
192 used to predict GPP, and coefficient of determination (R²), the root mean square error (RMSE, g
193 C m⁻² d⁻¹) and coefficient of variation (CV, %) was calculated. The average light use efficiency
194 at chlorophyll level (LUE_{chl}, i.e., ε̄_{chl}) was computed using GPP=LUE_{chl}*fAPAR_{chl}*PAR with a
195 least squares best fit algorithm. Improvements of crop daily GPP estimation using scaled VIs
196 were assessed.

197

198 III. RESULTS

199 The scaling factor (“a”, also called slope) and offset (“b”, also called y-intercept)
200 obtained through the regression functions fAPAR_{chl} =a*VI+b for each crop per field are listed in
201 Table 1, where the statistics for the R², RMSE and x-intercept are also summarized. The x-
202 intercepts of fAPAR_{chl} =a*VI+b give minimum VI values at zero fAPAR_{chl}. The 95% confidence
203 intervals of slope, y-intercept and x-intercept for each crop per field are reported, too. The CI_{green}
204 is a simple ratio index while the other three VIs include consideration of normalization. The
205 confidence intervals for CI_{green} are different from those for other three VIs for each type per field.
206 For each crop type in irrigated fields USNE1 and USNE2, the confidence intervals of y-
207 intercepts and x-intercepts for NDVI, EVI and CI_{green} are different from each other. For each

208 crop type in rainfed field USNE3, the confidence intervals of y-intercepts and x-intercepts for
209 NDVI and CI_{green} overlap each other, but are different from those for EVI. Mean values of the
210 confidence intervals of the slopes, y-intercepts and x-intercepts vary with VIs, sites, crop types
211 and irrigation options. None of the y-intercepts or x-intercepts for NDVI, EVI or $WDRVI_{green}$ is
212 close to the origin (i.e., zero X-Y point).

213 The functions in Tab. 1 were used to compute the scaled values of NDVI, EVI,
214 $WDRVI_{green}$ and CI_{green} for each crop type per field. For instance, for the NDVI at US-NE1:
215 scaled NDVI = 1.11*NDVI-0.29. The coefficients $\bar{\varepsilon}_0$ and $\bar{\varepsilon}$ and LUE_{chl} of each crop per field are
216 listed in Table 2. Corn LUE_{chl} is ~1.6 times of soybean LUE_{chl} (Tab. 2), which agrees with the
217 expectation that C4 plants have higher LUE than C3 plants (e.g., Prince, 1991), and explains why
218 maize displays a wider daily GPP range ($\sim 34 \text{ g C m}^{-2} \text{ d}^{-1}$) than soybean ($\sim 19 \text{ g C m}^{-2} \text{ d}^{-1}$) (Zhang
219 et al., 2014b). The coefficients $\bar{\varepsilon}_0$ and $\bar{\varepsilon}$ were applied to estimate crop daily GPP.

220 Figure 1 shows the estimated soybean daily GPP for the rainfed field US-NE3 using the
221 four original VIs with $\bar{\varepsilon}_0$ and the scaled VIs with $\bar{\varepsilon}$, compared to tower daily GPP. The scaled
222 NDVI, EVI and $WDRVI_{green}$ combined with $\bar{\varepsilon}$ had better GPP estimation performance than the
223 original counterparts, respectively, demonstrating higher R^2 and lower RMSE. Compared to the
224 original counterparts, the (scaled NDVI)*PAR, the (scaled EVI)*PAR and the (scaled
225 $WDRVI_{green}$)*PAR values were closer to 0 when GPP=0. The scaled CI_{green} did not provide
226 better GPP estimation than the original CI_{green} . In order to save pages, similar figures for US-NE1,
227 US-NE2 and figures for maize in US-NE3 are not presented in this paper.

228 Table 3 summarized the statistics (R^2 , RMSE and CV) for estimating crop daily GPP
229 using the original VIs with $\bar{\varepsilon}_0$ and the scaled VIs with $\bar{\varepsilon}$, respectively. These statistics show that

230 the best performance was obtained with the scaled EVI while the least successful performance
231 among the four scaled VIs was obtained with CI_{green} across the sites, crop types and irrigation/
232 rainfed options. For example at the US-NE1 site, scaled EVI and scaled CI_{green} had contrasting
233 best/worst performances in GPP estimation: R^2 : 0.88/ 0.77, RMSE: 2.92/4.05 g C m⁻² d⁻¹, and
234 CV: 19% / 26% (Tab. 3). GPP estimates for corn had better performance than for soybean using
235 scaled NDVI and EVI for sites US-NE2 and US-NE3. Better results might be achieved for the
236 sites examined in other studies (King et al., 2011; Sjöström et al., 2009) if the scaled EVI
237 (through coefficients obtained from the regression of fAPAR_{chl} vs. EVI) had been utilized.

238 For each crop in any field, the scaled NDVI, EVI and WDRVI_{green} improved the
239 prediction performance of crop daily GPP while the scaled CI_{green} did not, compared to the
240 original un-scaled VIs. GPP improvements for the three that benefited from scaling, ranked from
241 most to least were the NDVI, WDRVI_{green}, EVI, for which the R^2 increased (\uparrow : 0.16, 0.13, 0.09),
242 RMSE decreased (\downarrow : 0.95, 0.78, 0.65 g C m⁻² d⁻¹), and the CV also decreased (\downarrow : 8%, 6%, 5%).
243 The improvements also varied with crop types and irrigation conditions. For example, the NDVI
244 improvement for soybean (R^2 , \uparrow 0.20; CV, \downarrow 9%) was better than for corn (R^2 , \uparrow 0.13; CV, \downarrow 7%),
245 and the average improvement for the rainfed field (R^2 , \uparrow 0.21; RMSE, \downarrow 1.10 g C m⁻² d⁻¹; and CV,
246 \downarrow 10%) was better than for the irrigation fields (R^2 , \uparrow 0.12; RMSE, \downarrow 0.85 g C m⁻² d⁻¹; and
247 CV, \downarrow 6%).

248

249 IV. DISCUSSION

250 The PSROAIL2 model well distinguishes vegetation from soil and fAPAR_{chl} retrieved
251 with the PROSAIL2 model excludes the impact of soil/background (Zhang et al., 2012, 2013).

252 The fAPAR_{foliage} comprises chlorophyll and non-chlorophyll foliage fractions (fAPAR_{chl},
253 fAPAR_{non-chl}). Therefore, the PAR absorbed by non-photosynthetic vegetation components (NPV)
254 of the canopy is excluded from APAR_{chl} since APAR_{chl}=fAPAR_{chl}*PAR. This is the theoretical
255 basis for potential improvement of GPP estimation using the scaled VIs. The x-intercept values
256 of the semi-empirical linear functions of fAPAR_{chl} vs. VI in Table 1 have an important
257 biophysical meaning: there is not any chlorophyll showing up at the pixel when its un-scaled VI
258 is less than its x-intercept value. Gitelson and colleagues (Gitelson et al., 2007) reported that,
259 before green-up when green leaves do not appear, MODIS 250 m NDVI values for the fields
260 could be greater than 0.2, which is close to the minimum x-intercepts of NDVI (0.23, Tab. 1) we
261 found with MODIS 500 m images. In irrigated fields, the mean values of the x-intercept
262 confidence intervals for EVI were about half of those for NDVI, and about 1/3 as large as those
263 for WDRVI_{green} (Tab. 1). In rainfed fields, the mean values of the x-intercept confidence
264 intervals for EVI were about half of those for both NDVI and WDRVI_{green} (Tab. 1).
265 Soil/background wetness has less impact on EVI than on NDVI which is consistent with the
266 original idea that inspired the development of EVI (Huete, 1988; Huete et al., 1997). Daughtry et
267 al. (2000) has expressed that VIs combined with NIR and red bands are less impacted by
268 background than VIs combined with NIR and green bands. Earlier studies (Sims et al., 2006,
269 2008) have shown that GPP drops to zero at variable EVI values (i.e., x-intercept EVI values) in
270 their selected flux sites, and have found the minimum x-intercept value is ~0.1. So Sims et al.
271 (2008) has developed a GPP model using EVI – 0.1 instead of the original EVI. The x-intercept
272 confidence intervals of EVI in the three fields (US-NE1, US-NE2 and US-NE3) ranged from
273 (0.12, 0.13), (0.14, 0.15) to (0.16, 0.18). Our findings are consistent with earlier empirical studies
274 (Daughtry et al., 2000; Huete, 1988; Huete et al., 1997; Sims et al., 2006, 2008). Furthermore,

275 the scaled VIs with scaling factors and offsets using the semi-empirical relationships between
276 fAPAR_{chl} vs. VIs for each crop type per field are more physiologically meaningful (Tab. 1) than
277 the original un-scaled VIs.

278 The $\bar{\varepsilon}$ estimates for all scaled VIs are close to the relevant LUE_{chl} values for each crop
279 type per field. In contrast, the $\bar{\varepsilon}_0$ estimates associated with the original un-scaled NDVI and
280 WDRVI_{green} are lower than the relevant LUE_{chl} values. The $\bar{\varepsilon}_0$ estimates for CI_{green} are much
281 lower than the relevant LUE_{chl} values because the original un-scaled CI_{green} range (~1 to 10) is
282 much wider than the scaled CI_{green} range (~0 to ~1). It is worth noting that both the $\bar{\varepsilon}_0$ and the $\bar{\varepsilon}$
283 estimates for the original EVI and the scaled EVI are close to the physiologically relevant LUE_{chl}
284 values. This partly explains the reasonableness and success of the Vegetation Photosynthesis
285 Model (VPM) (Xiao et al., 2004) which assumes GPP = $\varepsilon \cdot EVI \cdot PAR$. This study suggests that the
286 GPP estimation made with the VPM may be improved by replacing the original EVI with
287 fAPAR_{chl}, or by scaling the EVI using the relationship between fAPAR_{chl} and EVI.

288 The R² between tower daily GPP and estimated GPP with scaled VIs for all cases ranges
289 from 0.66 to 0.88 while the RMSE (CV) between them ranges from 4.37 to 2.11 g C m⁻² d⁻¹
290 (from 31% to 17%). Although the R² between fAPAR_{chl} and scaled VI is high for all cases (0.73
291 – 0.97), the RMSE between fAPAR_{chl} and scaled VI varies with crop type, irrigation/rainfed
292 options, and VI options, which caused the variation of the performance of estimated GPP with
293 scaled VIs. Among the four scaled VIs, the RMSE between fAPAR_{chl} and the scaled EVI is
294 smallest and the R² is highest for all study sites. For US-NE2 and US-NE3, the RMSE between
295 fAPAR_{chl} and scaled CI_{green} is biggest and the R² is lowest.

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297

V. CONCLUSION

298 This study exhibited improvement in the performance of crop daily GPP estimation using
299 scaled NDVI, EVI and WDRVI_{green}, compared to their original un-scaled counterparts. However,
300 performance improvement of crop daily GPP estimation using scaled CI_{green} was not observed.
301 The irrigated fields have better performance, as compared to the rainfed field. The performance
302 also varied with crop types and VI options. The scaled EVI provided the best performance
303 among all cases. This study does not find that the scaled WDRVI_{green} or the scaled CI_{green} is
304 superior to the scaled NDVI or scaled EVI in predicting crop daily GPP.

305 Compared to the original VIs, the scaled VIs developed with the semi-empirical
306 relationships between fAPAR_{chl} and VIs are more physiologically meaningful. However, the
307 scaling factors and offsets (and x-intercepts) vary field by field, and vary type by type.
308 Investigations to explore the scaling factors and offsets of these VIs using fAPAR_{chl} for other
309 plant functional types should be carried out in the future. We will explore how the scaling factors
310 and offsets change over space and time, and vary with climate. Investigations on whether scaled
311 EVI is best for all fields and all types among the four scaled VIs are also needed. We suggest an
312 approach whereby MODIS-derived VIs are scaled pixel by pixel. This approach provides scaled
313 VIs for use when fAPAR_{chl} is unavailable. We expect that future research on GPP simulation
314 based on the biochemical or land surface modeling (Bounoua et al., 2000; Potter et al., 2003;
315 Sellers et al., 1994, 1996) will achieve reduced uncertainty and improved accuracy when the
316 scaled MODIS VIs replace the original VIs.

317

ACKNOWLEDGMENTS

318 This study was supported by NASA Terrestrial Ecology project (Grant No., NNX12AJ51G; PI,
319 Q. Zhang) and NASA Science of Terra and Aqua project (Grant No., NNX14AK50G; PI, Q.
320 Zhang) (Dr. Diane Wickland, manager). We would like to thank the support and the use of
321 facilities and equipment provided by the Center for Advanced Land Management Information
322 Technologies and the Carbon Sequestration program, University of Nebraska–Lincoln. Site-
323 specific climate and CO₂ flux data are distributed by AmeriFlux network
324 (<http://public.ornl.gov/ameriflux>), supported by Carbon Dioxide Information Analysis Center at
325 the Oak Ridge National Laboratory of the Department of Energy. We are grateful to anonymous
326 reviewers whose comments helped improve the paper.

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585 **Figure captions**

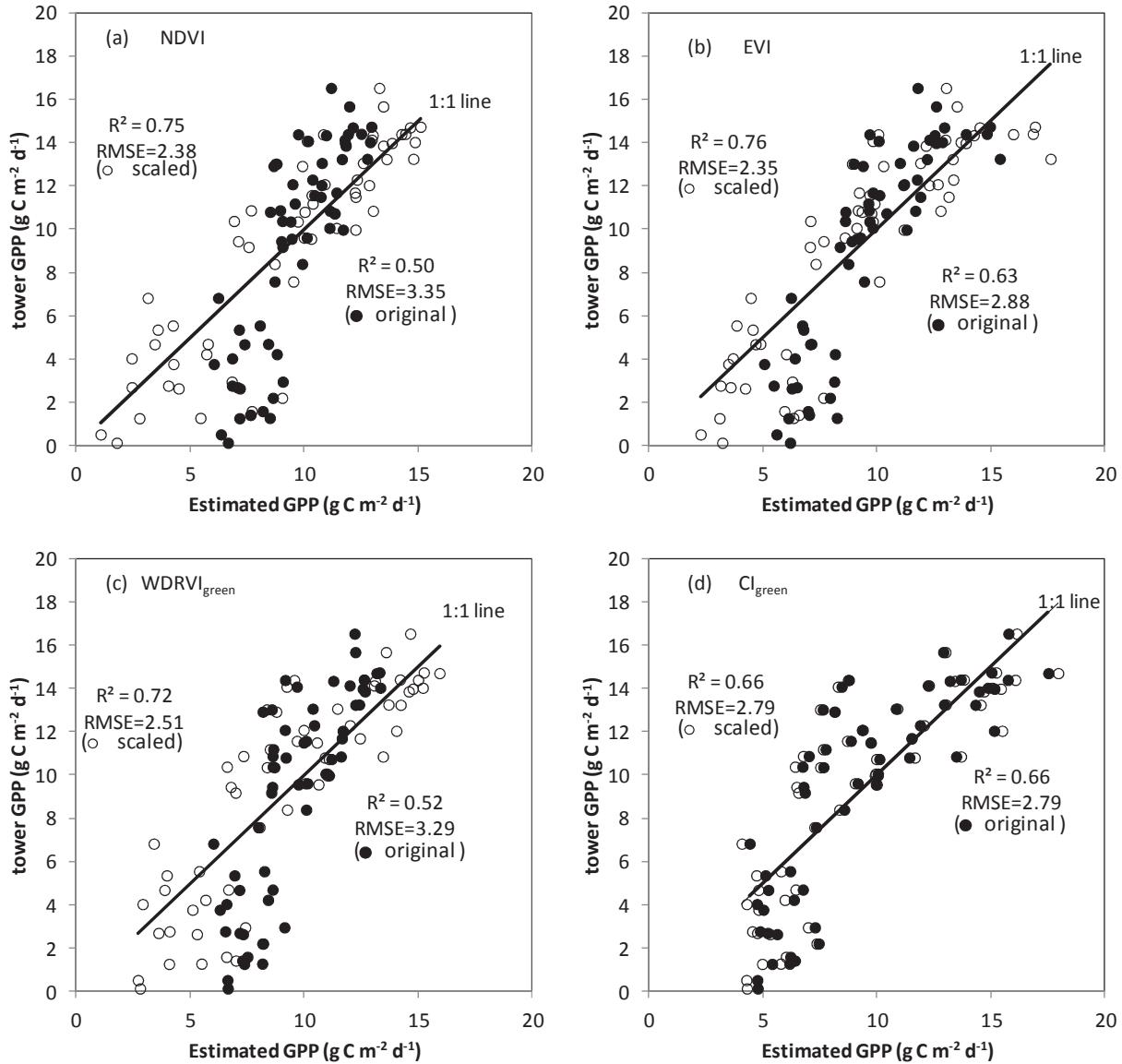
586 Figure 1. Comparison between tower daily GPP vs. estimated daily GPP for the US-NE3 site
587 (soybean): (a) NDVI; (b) EVI; (c) WDRVI_{green}; and (d) CI_{green}. Filled circles use original un-
588 scaled VIs while empty circles use scaled VIs. Only observations with VZA $\leq 35^\circ$ are included.

589 **Table captions**

590 Table 1. List of relationships between fAPAR_{chl} and VIs for the three crop sites ($y=ax+b$,
591 $y:fAPAR_{chl}$, $x:VI$). The 95% confidence intervals of slope (“a”), y-intercept (“b”), and x-
592 intercept are presented. Coefficients of determination (R^2) and root mean square error (RMSE)
593 are also presented.
594

595 Table 2. List of the coefficient $\bar{\varepsilon}_0$ in $GPP=\bar{\varepsilon}_0*VI*PAR$, the coefficient $\bar{\varepsilon}$ in $GPP=\bar{\varepsilon} *scaled$
596 $VI*PAR$, and LUE_{chl} in $GPP=LUE_{chl}*fAPAR_{chl}*PAR$ (unit: g C mol⁻¹ PPF)
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598 Table 3. Coefficients of determination (R^2), root mean square errors (RMSE, g C m⁻² d⁻¹) and
599 coefficients of variation (CV) for simulated GPP with the VIs using two options: original
600 unscaled VIs versus scaled VIs, compared to tower daily GPP
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623 scaled VIs while empty circles use scaled VIs. Only observations with VZA $\leq 35^\circ$ are included.

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Table 1. List of relationships between fAPAR_{chl} and VIs for the three crop sites (y=ax+b, y:fAPAR_{chl}, x:VI). The 95% confidence intervals of slope ("a"), y-intercept ("b"), and x-intercept are presented. Coefficients of determination (R^2) and root mean square error (RMSE) are also presented.

		NDVI	EVI	WDRVI _{green}	Cl _{green}
US-NE1 (maize, irrigated)	function	y=1.11x-0.29 (1.07, 1.14) slope 95% confidence interval y intercept 95% confidence interval x intercept 95% confidence interval	y=1.30x-0.18 (1.26, 1.34) (-0.20,-0.17) (0.14,0.15)	y=1.13x-0.39 (1.09,1.17) (-0.41,-0.37) (0.34,0.35)	y=0.13x-0.13 (0.12,0.13) (-0.14,-0.11) (0.92,1.04)
	R^2	0.95	0.96	0.94	0.94
	RMSE	0.06	0.05	0.06	0.06
US-NE2 (maize, irrigated)	function	y=1.10x-0.27 (1.07,1.14) slope 95% confidence interval y intercept 95% confidence interval x intercept 95% confidence interval	y=1.29x-0.16 (1.25,1.34) (-0.18,-0.15) (0.12,0.13)	y=1.11x-0.37 (1.07,1.15) (-0.40,-0.35) (0.33,0.34)	y=0.12x-0.10 (0.11,0.12) (-0.12,-0.08) (0.72,0.91)
	R^2	0.96	0.96	0.95	0.93
	RMSE	0.05	0.05	0.06	0.08
US-NE2 (soybean, irrigated)	function	y=1.06x-0.25 (1.03,1.10) slope 95% confidence interval y intercept 95% confidence interval x intercept 95% confidence interval	y=1.21x-0.16 (1.18,1.24) (-0.17,-0.14) (0.12,0.13)	y=1.04x-0.32 (1.00,1.08) (-0.34,-0.30) (0.30,0.31)	y=0.11x-0.08 (0.10,0.12) (-0.10,-0.06) (0.58,0.81)
	R^2	0.95	0.97	0.94	0.89
	RMSE	0.05	0.05	0.06	0.08
US-NE3 (maize, rainfed)	function	y=1.25x-0.43 (1.12,1.38) slope 95% confidence interval y intercept 95% confidence interval x intercept 95% confidence interval	y=1.46x-0.25 (1.34,1.59) (-0.30,-0.19) (0.16,0.18)	y=1.13x-0.39 (1.00,1.26) (-0.48,-0.30) (0.33,0.36)	y=0.11x-0.02 (0.10,0.13) (-0.08,0.04) (0.05,0.37)
	R^2	0.82	0.87	0.78	0.73
	RMSE	0.07	0.06	0.07	0.08
US-NE3 (soybean, rainfed)	function	y=1.29x-0.44 (1.18,1.40) slope 95% confidence interval y intercept 95% confidence interval x intercept 95% confidence interval	y=1.37x-0.24 (1.28,1.46) (-0.29,-0.19) (0.17,0.18)	y=1.07x-0.35 (0.95,1.19) (-0.44,-0.26) (0.31,0.35)	y=0.10x+0.03 (0.08,0.11) (-0.04,0.09) (-0.57,-0.02)
	R^2	0.91	0.94	0.85	0.77
	RMSE	0.06	0.05	0.08	0.10

Table 2. List of the coefficient $\bar{\varepsilon}_0$ in GPP= $\bar{\varepsilon}_0^*$ VI*PAR, the coefficient $\bar{\varepsilon}$ in GPP= $\bar{\varepsilon}^*$ scaled VI*PAR, and LUE_{chl} in GPP=LUE_{chl}*fAPAR_{chl}*PAR (unit: g C mol⁻¹ PPFD)

	LUE _{chl}	NDVI	EVI	WDRVI _{green}	CI _{green}
	$\bar{\varepsilon}_0$	$\bar{\varepsilon}$	$\bar{\varepsilon}_0$	$\bar{\varepsilon}$	$\bar{\varepsilon}_0$
UE-NE1 (corn, irrigated)	0.65	0.48	0.68	0.65	0.67
US-NE2 (corn, irrigated)	0.65	0.49	0.66	0.66	0.65
US-NE2 (soybean, irrigated)	0.42	0.31	0.43	0.40	0.42
US-NE3 (corn, rainfed)	0.71	0.45	0.73	0.67	0.72
US-NE3 (soybean, rainfed)	0.43	0.28	0.44	0.39	0.44

Table 3. Coefficients of determination (R^2), root mean square errors (RMSE, $\text{g C m}^{-2} \text{d}^{-1}$) and coefficients of variation (CV) for simulated GPP with the VIs using two options: original unscaled VIs versus scaled VIs, compared to tower daily GPP

		NDVI		EVI		WDRVI _{green}		CI _{green}	
		original	scaled	original	scaled	original	scaled	original	scaled
US-NE1	R^2	0.67	0.80	0.8	0.88	0.67	0.80	0.77	0.77
	RMSE	4.85	3.77	3.74	2.92	4.88	3.84	4.05	4.05
	CV	31%	24%	24%	19%	32%	25%	26%	26%
US-NE2 (corn)	R^2	0.72	0.81	0.83	0.88	0.71	0.77	0.72	0.72
	RMSE	4.38	3.62	3.4	2.83	4.42	3.95	4.39	4.37
	CV	26%	22%	21%	17%	27%	24%	26%	26%
US-NE2 (soybean)	R^2	0.63	0.78	0.75	0.84	0.65	0.79	0.73	0.73
	RMSE	3.16	2.45	2.61	2.11	3.09	2.43	2.76	2.75
	CV	31%	24%	26%	21%	30%	24%	27%	27%
US-NE3 (corn)	R^2	0.63	0.80	0.7	0.81	0.62	0.76	0.68	0.69
	RMSE	4.66	3.44	4.14	3.32	4.68	3.75	4.32	4.31
	CV	33%	25%	30%	24%	34%	27%	31%	31%
US-NE3 (soybean)	R^2	0.5	0.75	0.63	0.76	0.52	0.72	0.66	0.66
	RMSE	3.35	2.38	2.88	2.35	3.29	2.51	2.79	2.79
	CV	36%	26%	31%	26%	36%	27%	30%	30%